IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 6, Issue 3, March 2017

Optimal Face Retrieval From LFW Dataset

Priyanka A. Deshmukh[1], Prof. S.P. Abhang[2]

ME Scholar, Comp. Sci. &Engg, CSMSS college of engineering, Aurangabad, Maharashtra, India[1]

Asst. Prof, Dept of Comp. Sci. &Engg, CSMSS college of engineering, Aurangabad, Maharashtra, India[2]

Abstract: A method for face retrieval will proposed to describe. In most of the cases various methods are unable to increase retrieval rate of face images especially LFW images, by using this proposed system the retrieval rate increased. In face retrieval, objects of inter class should have larger distance than intra class objects. By extracting LBP & SIFT features of training image, shape context and inner distance shape contexts methods are applied on test image for deriving relevant images with better performance.In particular, when measures the input distance are quite different from the truth or the variance of data from the same class is too large, in such a condition, our proposed system will use the algorithm 'Optimal Face Retrieval'.

Keywords: LFW, IDSC,SIFT, LBP.

I. INTRODUCTION

The basic idea for the image retrieval techniques in image processing isContent based image retrieval (CBIR). Challenging work in image retrieval is providing a test image& extracting feature from that image on the basis of shape and color of given image, then comparing that image with the images from database using different techniques. While comparing features of the test imagewith the dataset, distance of interclass and intraclass should have to consider for retrieval of images.

In Co-transduction for shape retrieval framework[1], this combines two different distance metrics. With the same spirit as in co-transduction or in tri-transduction it combines three different distance metrics. The improvement in performance on large dataset has demonstrated the effectiveness of co-transduction/tri-transduction for retrieval of shape/object. But it did not significantly performed on LFW dataset9], which contains face images with different lightning poses, illuminations of nature. We use Scale Invariant Feature Transform (SIFT) algorithm to detect corners from face image, Local Binary Points (LBP) and Inner Distance and Shape Context (IDSC) to compare feature of test image with dataset images.

II. PREVIOUS WORK

To extend the idea of the traditional content based image retrieval systems to face images automate the face retrieval system is the one solution.During the past few years, content-based image retrieval(CBIR) has gained much attention for its potential applications in multimedia management[12].The users can ask for relevant images through query to the system by providing face images. The QBIC is a classic CBIR system which allows querying by simple query images and image properties like average color,color distribution and texture to retrieve the face images the user is looking for[13].

There are some content-based retrieval system which provides methods for searching several types of related image database, like PCA (Principle Component Analysis) as one of the key image feature for retrieval. Compression of the images using PCA is statistical in nature this restricts it to some extent[8].

In the last two decades, discrete wavelet transform (DWT) has been proven to be a powerful tool for texture analysis and representation. DWT decomposes an image into independent frequencybands exhibiting details and structures at multiple scales and orientations[14].

Divides each face image in adjacent region into blocks. To extractfeature from these blocks 2D Discrete Cosine Transform (DCT) applied and from these features histogram is generated for every region. Then comparison of image is done based on the difference of histogram.

The LDA approach or Fisher discriminants group images of the class and separates images of different classes Images are projected from N-dimensional space (where N is the number of pixels in the images)[8].

III. PROPOSED WORK

In our proposed system we worked on the limitations which are mentioned in our base paper Co-Transduction in Shape Retrieval[1] and we come up with relevant output. Architecture of proposed system is shown in fig. 1 below. The proposed system take an test image as input preprocessing filters perform ontest image and represents deriving SIFT and LBP features, the detail process is described below.

A. Preprocessing

In this module we removed the noise if any from input image. Noise is some unwanted things that contaminate an image, and is achieved by using median filter.

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 6, Issue 3, March 2017

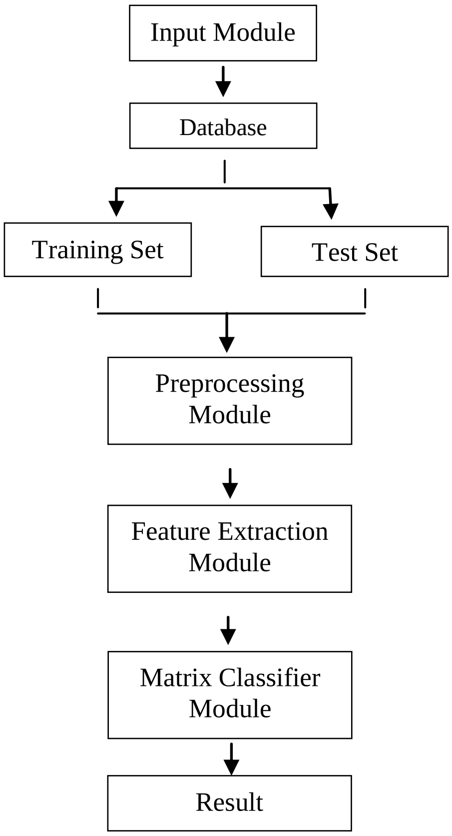


Fig. 1 Architecture of Proposed Work

B. Local Binary Pattern (LBP)

The Local Binary Pattern operator basically extract feature of texture. It also shown that this operator performs well on segmentation and image retrieval. To consider shape information of image, divide images into M small non-overlapping regions $R_0, R_{1....}R_M$ [6].The basic LBP operator assign to every pixel of 3x3 image window. For each pixel location value is compared to every pixel in its 8 neighboring pixel. This can start from any neighboring pixel and then can traverse either in clockwise or anti-clockwise direction. For each neighboring pixel comparisons will perform.

8	2	7
2	7	8
7	7	1

10110110 →

	182	

Fig. 2 Binary Representation

The result of thiscomparison will store in a 8-bit binary array.After calculating LBP mask values range from 0-255 as shown in fig. 2, so LBP normalized histogram of size 1-256 will perform. Then histogram extracted from each sub-region concatenated into single, spatially enhanced feature histogram, which defined as:

$$H_{ij} = \sum_{x,y} I(f_i(x,y)=i)\, I((x,y) \in R_j) \quad (1)$$

C. Scale Invarient Feature Transformation (SIFT)

To collect local scale invariant feature vectors transformed from the image the SIFT is use. These feature vectors acquired by the SIFT remains invariant under scaling, rotation or transformationon the image and variation in lightning condition. Any object represents many features, SIFT image feature vector provide a set of features that are not changed under any conditions. Using SIFTcan calculate feature vectors and identify various objects in different images.Transformations are used to match faces images in the dataset.

While considering an object to recognized in a larger image dataset, SIFT image features also allow objects to be recognizedfrom multiple images of the same location taken with different positions within the environment.

To obtain those features, SIFT algorithm works in steps. At first step, "scale function" is used to identify candidate keypoints. At this stage filtering attempts to identify those locations & scale which are identifiable from different views of the same object.

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \ (2)$$

Where, $L(x, y, \sigma)$ is the convolution of, $G(x, y, \sigma)$ andinput image$I(x, y)$ which is given by:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \qquad (3)$$

Now next step in SIFT is to eliminate low contrast keypoints which is given by[3]:

$$D(z) = D + \frac{1}{2}\frac{\partial D^{-1}}{\partial x} z (4)$$

To detect the local extremaof $D(x, y, \sigma)$ the ratio of principal curvature can be checked efficiently using following equation[3].

$$\frac{D_{xx} + D_{yy}}{D_{xx}\, D_{yy} - (D_{xy})^2} < \frac{(r+1)^2}{r} \qquad (5)$$

If the function value at **z** is below a threshold value then this point is eliminated.

The next step is to detect possible orientation of image. Here each keypoint is assigned one or more orientation based on local image gradient magnitude and orientation which is given by following equation:

$$m(x,y)= \sqrt{(I(x+1,y) - I(x-1,y))^2 + (I(x,y+1) - I(x,y-1))^2} \ (6)$$

$$\theta(x,y) = \tan^{-1}\{\frac{I(x,y+1) - I(x,y-1)}{I(x+1,y) - I(x-1,y)}\} \qquad (7)$$

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 6, Issue 3, March 2017

We use these feature extraction equations from [3][5].

D. Inner Distance and Shape Context (IDSC)

In our proposed work to find shortest path within imagewe added the inner-distancewith SIFT and LBP, defined as the length of the shortest path within the shape articulation.For example, in given Fig. 3, the points on shape (a) ,(b) and (c) have similar spatial distributions, they are quite different in their part structure. The inner-distance between the two marked points in given shape is quite different in (a) and (c), while almost same in (c) and (b). This example given below shows that the inner-distance is insensitive to shape articulation and sensitive to part structures, a desirable property for complex shape comparison [11]. In this example, it is clear thatwithout dividing shapes into parts the inner-distance works on part structure of shape.

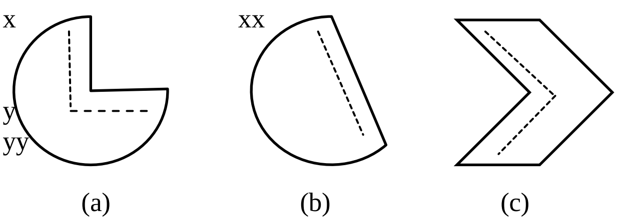


Fig. 3Three objects with the dashed lines denote shortest paths within the shape boundary that connect landmark points.

First, we define a shape G as a connected and closed subset. Given a shape G and two points x; y ϵ G, relative orientation denoted as α(x,y ;G) and the inner-distance between x; y, denoted as L(x,y;G), is defined as the length of the shortest path connecting x and y within G. One example is shown in Fig. 4.

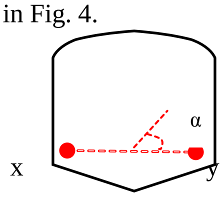


Fig.4 Definition of the inner-distance. The dashed line shows the shortest path between point x and y.

E. Optimal Face Representation:

Extracting the LBP and SIFT features of input images and represented it by matrix. A basic problem in object retrieval is to use labeled training samples from distinct object classes and to correctly determine an object to which a new test sample belongs. We arrange the samples of training images in a matrix such that every column of matrix represents features of images.

Algorithm: Optimal Face Retrieval from LFW Dataset

1. Input: Training Image I
2. Initialize I
3. Assume ω ← window, C_{xy}pixels ← processed,
4. forω_{min} , ω_{med} , ω_{max} ,**do**
5. ifω_{min}<C_{xy}<ω_{max}**then**$C_{xy}$is constant **else**
6. $C_{xy}$is noisy
7. if$C_{xy}$is noisy &ω_{min}<ω_{med}<ω_{max}**then**
8.C_{xy} =ω_{med}
9. end if
10. ifω_{med} is noisy **then**
11. C_{xy} = mean(C_{xy});
12. end if
13. I = C_{xy}
14. end if
15.end for
16. foreach image I in the training image , Initialize the pattern histogram, h = 0
17. Divide Image I into region
18. foreach centre pixel C_{xy}ôf I
19.I(x,y) = LBP mask
20. **end for**
21.h ← histogram of the mask I(x,y).
22. Z ∅ ← the set of local extrema of I(x,y)
23. foreach point I(x,y, σ) of extrema**do**
24. $Z = -\left(\frac{\partial^2 I}{\partial x^2}\right)^{-1}\frac{\partial I}{\partial x}$
25. if Z> 0 locate Minima , Z<0 locate maxima(// To computeextrema and $\frac{D_{xx}+D_{yy}}{D_{xx}\ D_{yy}-(D_{xy})^2}<\frac{(r+1)^2}{r}$
(// Eliminates unstable keypoints)
26. **end if**
27. **end for**
28. for smoothed image I(x,y, σ) at scale σ, find m(x,y) andθ(x,y)
29.G ← θ(x,y)
30.hhistogram of the relative orientations along G
31. end for
32. for each G(i; j)
33. P={∅} ← set of visited vertices
34. T={G(i ,j)} ← set of all unvisited vertices
35. L(x)={∅} label of shortest path
36.forselect v from T with smallest label for all i ,j ∈ T and i ≠ j**then**
37. P= P ∪{v} and T=T-{v}
38. **if** v=j then L(x)=w(v,j) **else**
39. Selectnext vertex from T ,
40. L(x)=min{ old L(x),L(v)+w(v,x)}
41.end for
42.end for

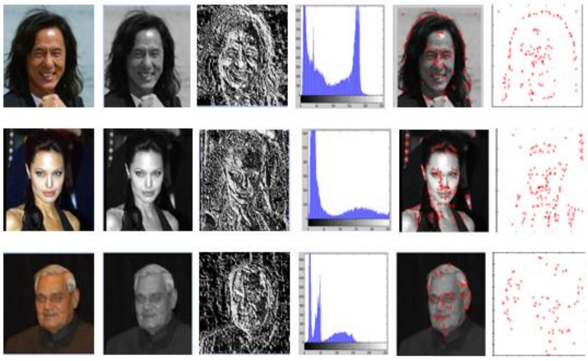
IV. EXPERIMENTAL RESULT

We loada database in classified format with complete training dataset. Then test image or input image is given as inputand it get processed as shown in our figure 1 which is Architecture of proposed work such as operation like pre-processing, LBP and SIFT feature extraction and then successfully retrieve relevant images to test image from the database. Here, figure 5 shows some sample test images with their noise removed , LBP featured images and histogram of it, SIFT image with corner points on the images.

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 6, Issue 3, March 2017



Test Image | Median Filter | LBP Image | LBP Histogram | SIFT Image | SIFT FP's

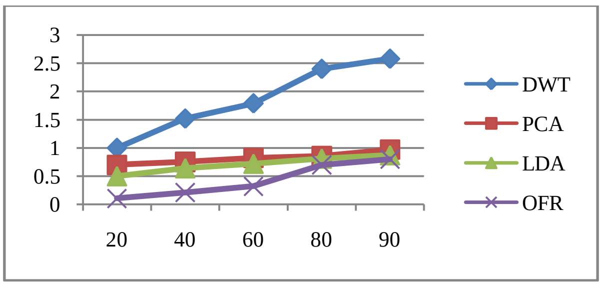
Figure.5Images with their LBP and SIFT Features.

We generate a graph of performance on by considering time required to retrieve the relevant images from the dataset corresponding to the total number of images in to given dataset.The graph shows in figure. 6, is the time required to retrieve images from the dataset which is directly proportional to the total number of images in dataset.For retrieval of the correct person's image from the database and to retrieve it there are many methods, our work efficiently reduced retrieval time by comparingwith some of previous methods like DWT, PCA, LDA.The comparison of these methods with our OFR is shows in Table 1 & figure 6 shows graphical representation of table 1.

Table 1.Comparison Table

Number of Images	20	40	60	80	100
Methods	Time in Sec				
LDA	0.5	0.64	0.72	0.81	0.87
PCA	0.7	0.753	0.823	0.854	0.97
DWT	1	1.52	1.79	2.4	2.58
OFR	**0.1**	**0.21**	**0.32**	**0.7**	**0.8**

Time in Sec



No of Images

Figure 6.Comparison of Retrieval Time For Various Algorithm

V. CONCLUSION

In this proposed work, we provide an efficient method for face retrieval by combining three different algorithms SIFT, LBP and IDSC. Through this work we successfully retrieve the face images from trained dataset of Labeled Faces in Wild (LFW) images achieving better retrieval rate.

As we worked on static dataset, further we can enhance our work by providing dynamicity to the database and test image by adding modules for image acquisition through camera and cropping techniques for resizing them.

REFERENCES

[1] Xiang Bai, Bo Wang, Cong Yao, Wenyu Liu, and ZhuowenTu, "Co-Transduction for Shape Retrieval" IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 21, NO. 5, MAY 2011

[2] Amrit Kumar Agrawal, YogendraNarain Singh, "Evaluation of Face Retrieval Methods in Unconstrained Environments", International Conference on Intelligent Computing, Communication & Convergence (ICCC-2015).

[3] JyotiKumari, R.Rajesha, KM.Pooja "Facial expression retrieval: A survey", Second International Symposium on Computer Vision and the Internet, 2015.

[4] Abdul HarisRangkuti, ZulfanyErlisaRasjid, DJunaidiSantoso, " Batik image classification using treeval and treefit as decision tree function in optimizing content based batik image retrieval" International Conference on Computer Science and Computational Intelligence (ICCSCI 2015).

[5] Hitdesh Kumar, Padmavati, " FaceRetrieval using SIFT by varying Distance calculation Matching Method", in International Journal of Computer Application volume 47-No.3, June 2012.

[6] Jo Chang-Yeon, " Face Detection using LBP features", Tran. On PAMI December 2008.

[7] BogdanSmolka and Karolina Nurzynska, "Power LBP: A novel texture operator for smiling and neutral facial display classification", ICCS 2015 International Conference On computational Science.

[8] N. Lavanyadevi, SP. Priya & K. Krishanthana, " Performance Analysis of Face Matching and Retrieval In Forensic Application".

[9] Gary B. Huang, Marwan Mattar, Tamara Berg, and Erik Learned-Miller, "Labeled Faces in the Wild: A Database for Studying Face Retrieval in Unconstrained Environments".

[10] Haibin Ling & David W. Jacobs ," Shape Classification Using the Inner-Distance". Center for Automation Research and Computer Science Department University of Maryland.

[11] Shape Classification Using the Inner-Distance Haibin Ling David W. Jacobs Center for Automation Research and Computer Science Department University of Maryland, College Park bling, djacobsg@ umiacs.umd.edu.

[12] "Semisupervised Biased Maximum MarginAnalysis for Interactive Image Retrieval", Lining Zhang, Student Member, IEEE, LipoWang, Senior Member, IEEE, and Weisi Lin, Senior Member, IEEE.

[13] "Fast Query Point Movement Techniquesfor Large CBIR Systems", Danzhou Liu, Member, IEEE, Kien A. Hua, Fellow, IEEE,Khanh Vu, and Ning Yu, Member, IEEE.

[14] "Wavelet Modeling Using Finite Mixtures ofGeneralized Gaussian Distributions: Application to Texture Discrimination and Retrieval",MohandSaïdAllili, Member, IEEE.